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Modelling Land Use and Land Cover Change for Sustainable Urban Futures: A Case Study of Pune

Ashlin Joseph, Mahesha D B*

School of Life Sciences, Mysuru, JSS Academy of Higher Education and Research, Mysuru
* Corresponding author email: maheshdivana@gmail.com

Abstract:

The occurrence of rapid urbanization in most developing cities as is the case with the urban agglomeration being examined has had a strong implication in the pattern of land-use and land-cover (LULC), which have sparked large scale effects on the environment and ecological condition. The current study examines the spatio temporal change of LULC in Pune City of India using a multi-temporal satellite imagery and a geospatial modelling framework. The findings obtained were LULC maps were created in 2010, 2015, 2020, and 2025 on the basis of the Landsat and Sentinel-2 images. The classification performance delivered All-over accuracies of 85.12 -96.02 per cent along with Kappa of 0.78-0.80, and hence validated the reliability of outputs. The change-detection analysis showed intense urbanization during the period of the 15 years. The built-up areas have continued to rise, receiving 119.96 km2 up to 161.08 km 2of land by 2010-2025, which constitutes an absolute difference of 41.12km2. On the other hand, scrubland was reduced by 49.88 km2 and barren land was reduced by 13.90 km2. The vegetation showed a moderate increase of 21.25km2 and the water bodies declined marginally by 0.50km2. Future LULC scenarios of the calendar year 2030 and 2040 were created by an Artificial Neural Network Cellular Automata (ANNCA) framework implemented on the MOLUSCE QGIS plugin. The drivers used in the model were elevation, slope, closeness to road networks, proximity to stream networks and distance to the urban core. The predictive maps created produced the total accuracy of 99.97% and Kappa of 0.9995, which reflects a high level of alignment with observations. Such simulations show that the regions will continue to dominate with the other categories of land-cover classes experiencing insignificant changes, but as this implies there might be a slow stabilization of urban growth.

Keywords: Land Use Land Cover, Urban Expansion, Remote Sensing, ANN-CA Modelling, MOLUSCE, Pune City

1. Introduction:

Land use and land cover (LULC) change is one of the key indicators of human impact on the natural environment and has come to become a defining point in the field of study of global environmental change. Rapid urbanisation, population growth, industrialization and the spread of infrastructures have enhanced transgression of the natural landscape into built matrix and highly felt in the rapidly developing countries. These changes are usually linked to the loss of agricultural lands, reduction in vegetative cover, and corrosion of environmental, such as urban heat islands, surface runoff, and ecosystem erosion. It follows that, an in-depth insight into the dynamics of LULC is essential to the development of viable urban planning and management of resources (Lambin et al., 2001; Turner et al., 2007).

The development of remote savoury systems and geographic information system (GIS) has gone a long way in enhancing the ability to track and examine the dynamics of LULC over time. The satellite imagery also provides synoptic, repetitive, and spatially sound observations of the surface of the Earth, which helps the researchers to observe landscape shifts in the range of temporal scales. The remote sensing data when implemented together with GIS-based spatial analysis tools allow a thorough evaluation of the trend in urban expansion and land transformation procedures (Lu et al., 2004; Coppin et al., 2004). As the by-

products, therefore, these technologies are critical components in the evaluation of the transformation in land-use in the past and in explaining the spatial distribution that comes with urban expansion.

In addition to plotting historic changes, the future projection of land-use patterns has taken an increasing relevance as a factor in the planning of sustainable urban development. Cellular Automata (CA) and spatially explicit modeling models have been widely used in the area of land-use simulation because they have the capability of incorporating neighbourhood effects and space effects which mediate land-transformation processes. CA-based models represent the change in land-use through application of transitioning rules that govern the development of land parcels depending on the use of neighboring land-uses and environmental contexts (Clarke et al., 1997; Batty et al., 1999). These models can also require intricate nonlinear connections between changes in land-use and their causal variables, such as accessibility, terrain qualities, and propinquity to the infrastructural features, when combined with machine-learned modeling schemes, like Artificial Neural Networks (ANN) (Li and Yeh, 2002).

The recent research has indicated the usefulness of integrating remote sensing, GIS, and spatial simulation models to examine urban development and forecast future LULC. These modeling systems can be used to define possible expansion paths and support the decision-making towards sustainable land utilization and urban development (Verburg et al., 2004; Liu et al., 2014). These prognostic models can also be critically useful in developing urbanisation cities that are rapidly developing cities, hence the need to measure future land-transformation processes and the environmental effects associated with unmanageable urban growth.

The City of Pune in Maharashtra, India, has witnessed a tremendous urbanization in the last several decades due to increasing economic growth, spread of information technology industries, and population pressure. The urbanisation has brought about drastic changes in the land-use patterns, especially the previously agricultural land and open space will be developed into a built up space. Here, the current paper examines the spatio-temporal changes in LULC in Pune City through the application of multispectral satellite data in 2010, 2015, 20, 2020, and 2025. The analysis also assesses the effect of the main spatial driving forces such as elevation, slope, distance to roads, distance to streams and distance to the city centre on change in land-use. Also, an Artificial Neural Network- Cellular Automation (ANN -Cellular Automation) modelling model deployed through MOLUSCE plug-in in QGIS is used to forecast future land-use scenarios in 2030 and 2040 to explain future trends of urban development and assist in the sustainable city planning approaches of Pune.

2. Study Area:

Pune is one of the fast growing metro centres in western India and Maharashtra Province. The city lies at an average elevation of about 560 above mean sea level between 18 o 25 -18 o 40 N and 73 o 45 -73 o 57 E, with the city lying at the leeward side of Western Ghats. Pune is located on the basin of the river Mula–Mutha which passes through the city and eventually joins the Bhima River. The climatic conditions are tropical wet-and-dry, and the average rainfall is approximately 700-800mm/year, which mainly falls during southwest monsoons. However, as revealed in the Census of India 2011, the city of Pune has experienced massive population growth and urbanization in the past several decades. This has led to enormous changes in land-use and land-cover due to this rapid urbanisation that has been boosted by the growth of industrialisation, education systems, and the development of the information technology sector (Ramachandra et al., 2015; Taubenböck et al., 2012).

3. Materials and Methods:

3.1 Data Used:

Multitemporal satellite data was used to investigate dynamism of LULC in Pune. In the case of the base-year 2010, the Landsat 5 image with a spatial resolution of 30m was used, but the Sentinel -2 image with a spatial resolution of 10m was used in the years 2015, 2020, and 2025. These data sets offer multi-spectral data that can be used to classify land-covers accurately and make time-related analyses. Besides satellite imagery, a number of spatial datasets were used as drivers of modeling land-use change such as digital elevation data to derive elevation and slope, and the use of vegetor layers of roads, streams, and the city centre to drive distance based variables. The analysis and modelling of all spatial datasets were projected

to a shared coordinate system and resampling of the dataset was done to ensure spatial consistency between data.

Table 1 : Data used for the study.

Data	Parameter	Year(s)	Source
Landsat-5	LULC classification	2010	Google Earth Engine (GEE)
Sentinel-2	LULC classification	2015, 2020, 2025	Google Earth Engine (GEE)
DEM	Elevation	—	USGS Earth Explorer
DEM-derived slope	Slope	—	Derived from DEM (QGIS)
Road network	Distance from roads	—	OpenStreetMap (OSM)
Stream network	Distance from streams	—	OpenStreetMap (OSM)
City centre	Distance from city centre	—	
Study area boundary	Administrative boundary	—	Digitized in QGIS

3.2 Methodology :

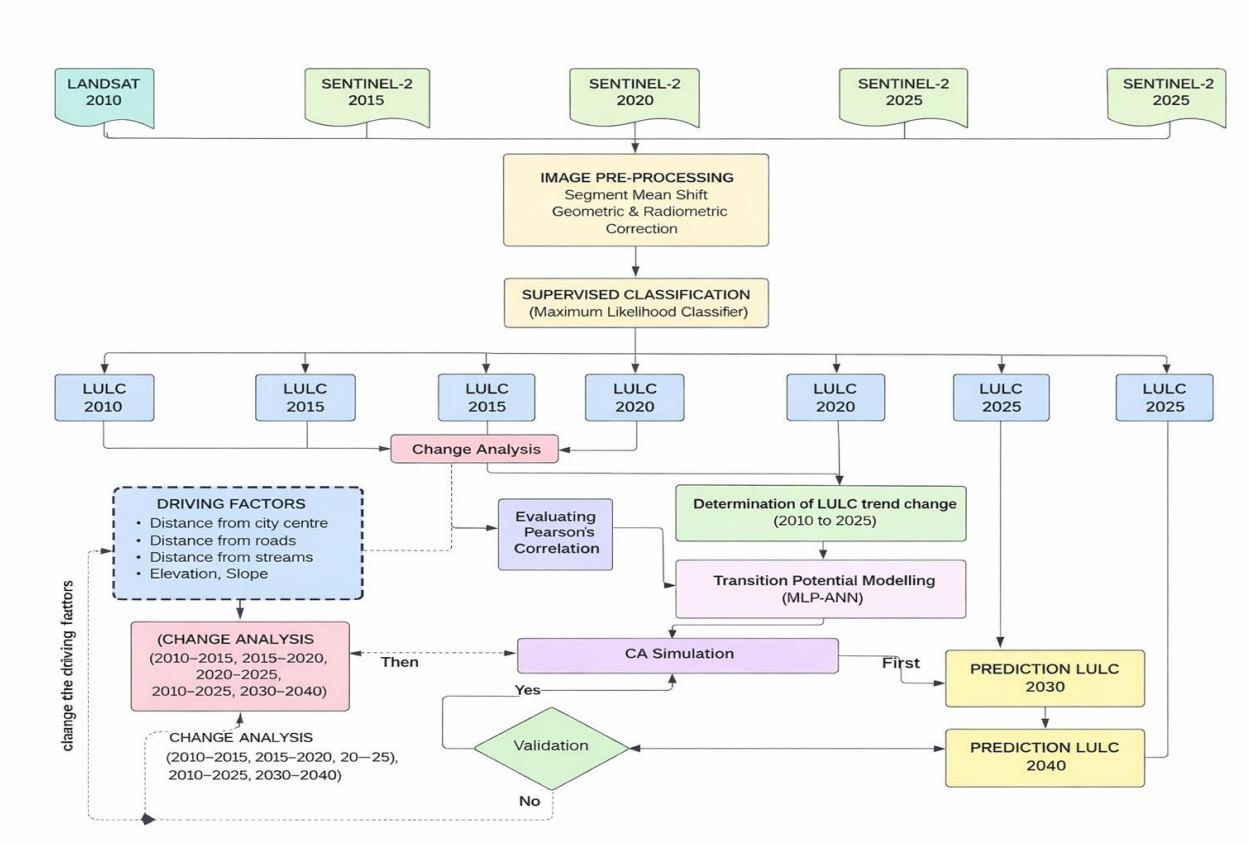


Figure 1: Flowchart of Methodology

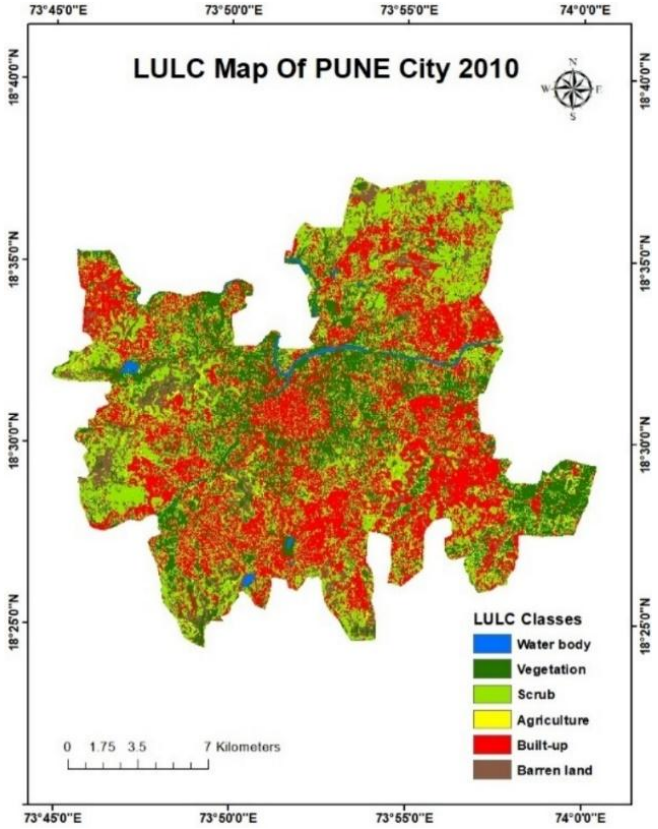
The multi-temporal satellites to capture the dynamics of land use and land cover (LULC) in Pune in 2010, 2015, 2020 and 2025 (Figure 1). The image of Landsat-5 was used in the 2010 period and image with higher resolution obtained by Sentinel-2 were used in the successive periods. Geometric and radiometric fixes of all pictures were done before the segmentation model using the Mean Shift algorithm. LULC maps of each year were produced by the supervised classification with the help of Maximum Likelihood Classifier (MLC). The assessment of the changes in the land use between the periods of 2010-2015, 20152020, and

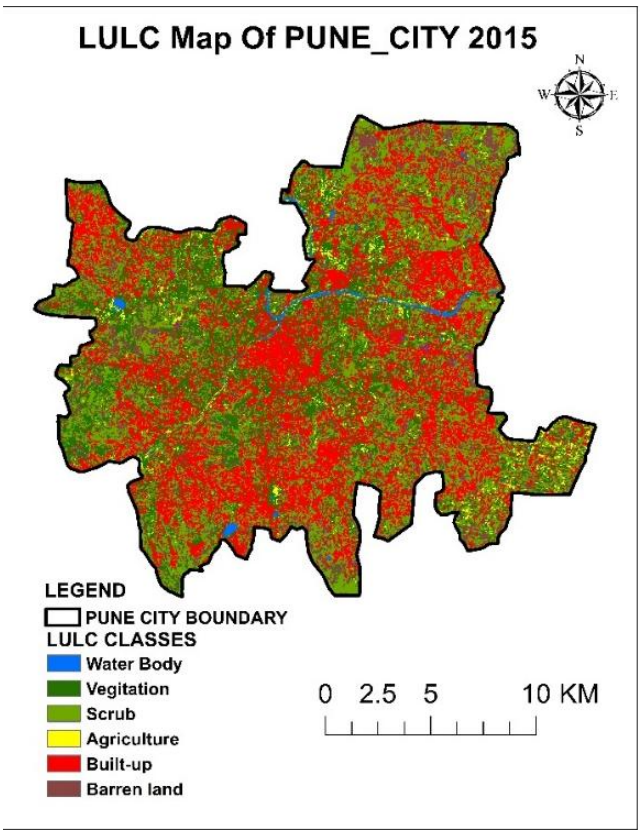
20202025 was made possible with the intention of post-classification comparison. The distance to city centre, distance to roads, distance to streams, elevation, and slope were spatial driving variables that were introduced and analyzed through Pearson correlation analysis. The estimation of transition potentials of classes of land use was then conducted using Multi-layer Perceptron Artificial Neural Network (MLP-ANN) model. The resultant transition probabilities were incorporated into a Cellular Automata (CA) framework to model dynamics of spatial land use: the calibrated model was subsequently used to project future LULC dynamics in 2030 and 2040.

Table 2: LULC classes

LULC Class	Description
Water bodies	Includes rivers, lakes, reservoirs, ponds, and other permanent surface water features
Vegetation	Areas covered by natural vegetation such as forests, plantations, grasslands, and dense green cover
Scrub	Land dominated by sparse vegetation, shrubs, bushes, and degraded vegetative cover
Agriculture	Croplands and agricultural fields under seasonal or perennial cultivation
Built-up	Urban and rural settlements, residential areas, commercial zones, industrial areas, and transportation infrastructure
Barren land	Unvegetated or sparsely vegetated land such as rocky surfaces, wastelands, exposed soil, and uncultivable areas

4. Results and Discussions





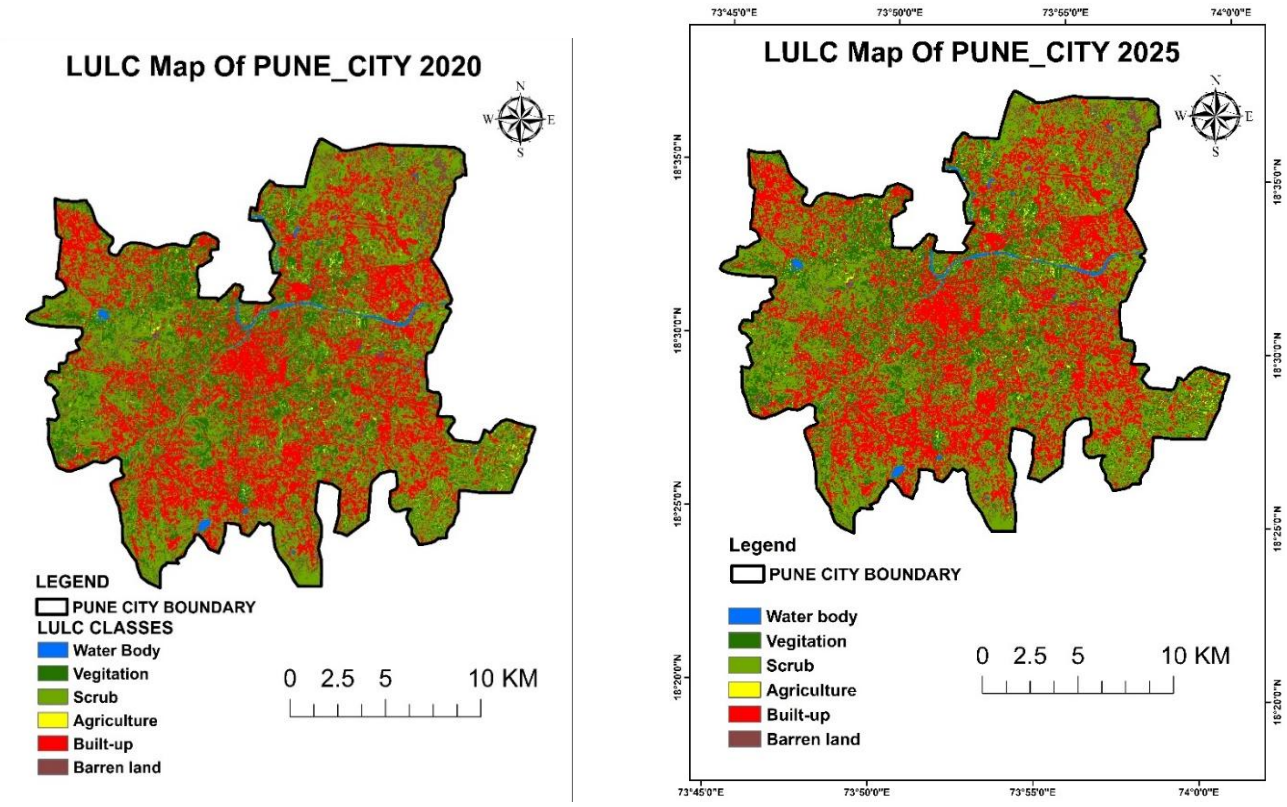


Figure 2: LULC maps of Pune for the year 2010,2015,2020 and 2025.

4.1 LULC Mapping and Accuracy Assessment:

Based on the Landsat5 and Sentinel-2 imagery, multi-temporal LULC maps were created in the years 2010, 2015, 2020 and 2025 in Pune (Figure 2). The Maximum Likelihood Classifier used to classify by major land cover. A confusion matrix and reference samples were used in the classification accuracy. The general classification rate changed between 85. 0 to 86.0concordance was good between the classified outputs and the reference data. The coefficients of the Kappa were between 0.78 and 0.80 indicating the presence of high levels of agreement in the absence of chance.

4.2 Driving Factors:

Five spatial variables were used to represent changes in land use and land cover (LULC) in Pune (Figure 3). The terrain constraints were indicated by topographical data: the elevation and the slope as obtained by Digital Elevation Model (DEM) data: the terrain areas with high elevation and steepness tend to have little land transformation. The variables concerning accessibility such as distance to roads were also included which affects urban sprawl as a result of improved connectivity and the development of infrastructure. Hydrological constraints were depicted by distance to streams since at times, development close to streams is limited because of flood risks and environmental laws. Also, deprivation to the city centre recorded the core-periphery urban development trends, where the normal development intensity decreases as the distance moves further off the core. The MOLUSCE model was used to study and simulate LULC transitions using these five spatial variables as inputs into the modeling system.

4.3 Pearson Correlation Analysis:

The Pearson correlation was used to test the association between the LULC transitions and the driving factors chosen (Table 3). As was conceived, the variables were the distance to the city centre, elevation (DEM), distance to roads, slope and distance to streams. The values of the correlation coefficients were

between -0.0112 and 0.5559 showing that the factors were associated with varying degrees of commitment. The positive relations between the topographic factors and accessibility ones were seen to be relatively higher with a positive correlation between DEM and slope (0.5559) and between distance of the centre and distance of the roads (0.4103), which proposes the idea of medium relationships. Correlations between most of the other variables were weak, which shows that there is not a lot of ground regarding redundancy of driving factors. The findings affirm that the variables are useful in presenting topography as well as accessibility gradients in the transition of land use, thus legitimizing their capability to simulate LULC dynamics using the MOLUSCE-based Cellular Automata simulation model.

Table 3 : Driving Factors with Persons 'Corelation

Driving Factor	Distance From Centre	DEM	Distance From Roads	Slope	Distance From Streams
Distance From Centre	—	0.2358	0.4103	0.1230	0.3796
DEM	__	—	0.1395	0.5559	-0.0112
Distance From Roads	__	__	__	0.06235	0.2179
Slope	__	__	__	—	0.001
Distance From Streams	__	__	__	__	—

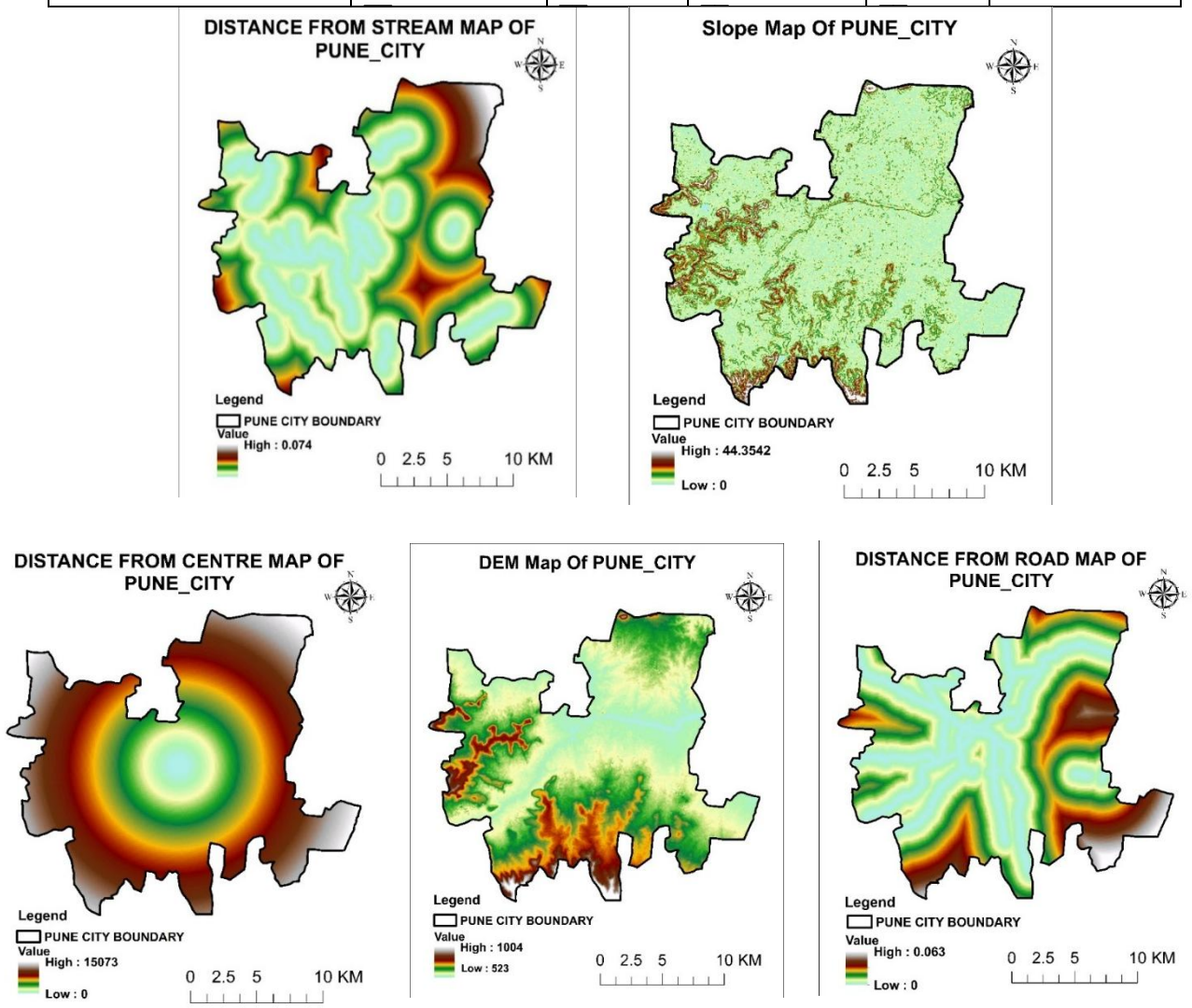


Figure 3: Driving factors of LULC change.

4.4 Transition Potential Modelling:

The appearance of transition potential studied the variations in LULC through time periods in Pune. The strongest growth rate in Built-up Land (BL) was registered between 2010 and 2015 as it grew by 5.47 km 2 (1.52 %) which demonstrates the rising urbanization. The water bodies (WB) and vegetation (VN) registered only 0.87 km 2 and 0.76 km2, respectively, whereas agricultural land (AR) lost considerably (4.92km 2). A massive land conversion is present in 2015-2020, as Settlement/ Built surfaces (SB) rose by 39.96 11.11% km 2, showing a significant growth in urbanization. On the other hand, vegetation (VN) and barren land (BL) shrank by 15.87km2 and 15.65km2, respectively, whereas the agricultural land was still shrinking. Between 2020-2025, the land use alteration was minor. Settlement/ Built surfaces (SB) increased slightly by 0.45km^2 by 155.72 km^2 but all other categories experienced marginal changes including water bodies, vegetation, agricultural land and barren land. These trends indicate a slow stabilization of patterns in land use with great urban growth in the past.

4.5 Change detection 2010 2025:

The change analysis of LULC between 2010 and 2025 shows that Built-up areas (BU) expanded by 41.12km 2 (11.46 per cent) showing rapid development of Pune within the period of 15 years. Vegetation (VN) grew by 21.25 km 2 (5.92 per cent) which could be explained by the planting efforts, increased observation, or the creation of green areas around urban agglomerations. Scrub land (SB) had the most significant decline of 49.88km 2 (-13.91%), which was mainly used to construct built-up and vegetated land. Agricultural land (AR) had a marginal of 1.92 km² (0.53%%), which showed the stability of the land with certain increases in the outer urban areas. There was a decrease of 13.90 km 2 of barren land (BL) -3.87 per cent. as development or vegetation cover expanded. Doubling water bodies (WB) decreased slightly (0.50 km 2 -0.13 percent), which is an indication of less stress on water resources since the water bodies experienced a minimal depreciation.

Table 4.2010 to 2025 LULC change

Classes	2010	2025	Total Area Change in Km	2010%	2025%	Total Change in %
WB	3.00 sq. km.	2.50 sq. km	-0.50 sq. km	0.83%	0.69%	-0.13%
VN	69.46 sq. km	90.71 sq. km	21.25 sq. km	19.37%	25.29%	5.92%
SB	116.35 sq. km.	66.47 sq. km	-49.88 sq. km	32.45%	18.54%	-13.91%
AR	12.14 sq. km.	14.06 sq. km	1.92 sq. km	3.38%	3.92%	0.53%
BU	119.96 sq. km.	161.08 sq. km	41.12 sq. km	33.45%	44.92%	11.46%
BL	37.62 sq. km.	23.72 sq. km	-13.90 sq. km	10.49%	6.61%	-3.87%

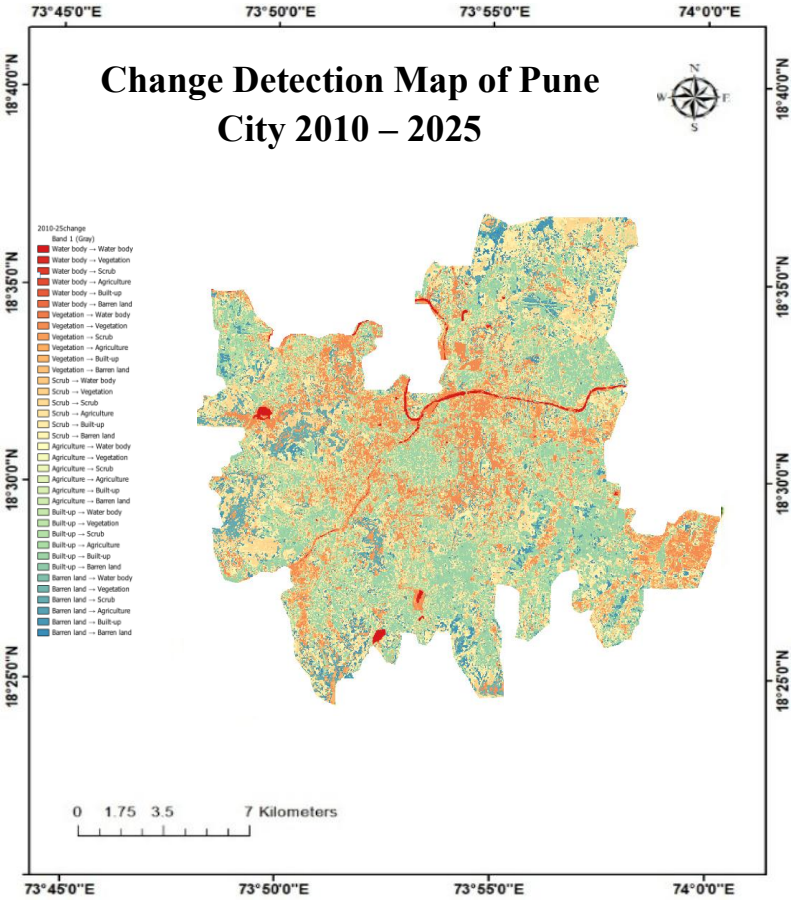


Figure 4. Change Detection 2010 – 2025 map

4.6ANN- Learning Curve Analysis:

The plot of the learning curve ***(Figure.5)*** shows a strong decrease in error in the early stages of the process, which means that the model is effectively trained. This is because convergence of the training and validation errors identifies convergence of the neural network. The fact that the two curves are similar proves that it has strong generalization and less over-fitting.

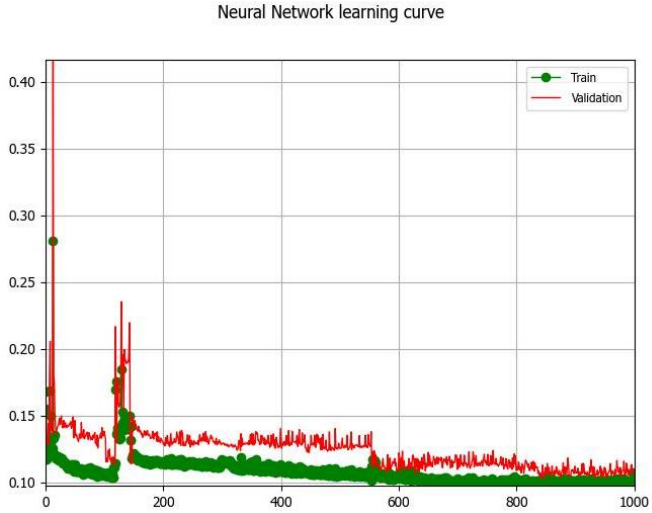


Figure.5 Neural Network curve for 2010-25

4.7 Simulation and Prediction of LULC for 2030 and 2040:

Using the artificial neural network cellular automata (ANN-CA) MOLUSCE framework, future LULC projection was simulated to 2030 and 2040 in Pune based on historical land-use and land-cover (LULC) pattern and driving factors (Figure 6). According to the results of the simulation, it can be concluded that the built-up areas will continue to grow, which denotes the further development of the city and the growth of the pressure of urbanization. On the other hand, the vegetation, arid land, and agricultural classes will enjoy a slow degradation as a result of urban infrastructure construction and residential development. There are relatively small changes of water bodies during the period concerned. It is anticipated that these projected LULC maps help understand the possible spatial formations of urban growth and may guide on future construction of urban planning and sustainable land management in Pune. Validation outcome shows that predicted and observed LULC maps are very much consistent; overall accuracy of 99.97 per cent and Kappa coefficient of 0.9995 are clearly indicating virtual perfection other than just by chance. Additional evidence of high class or spatial concordance in LULC transitions is that in the Kappa histogram (0.99952) and the Kappa location (0.99998), the values are substantial. These findings confirm that ANN route model in predicting future land-use and CA MOLUSCE are highly reliable.

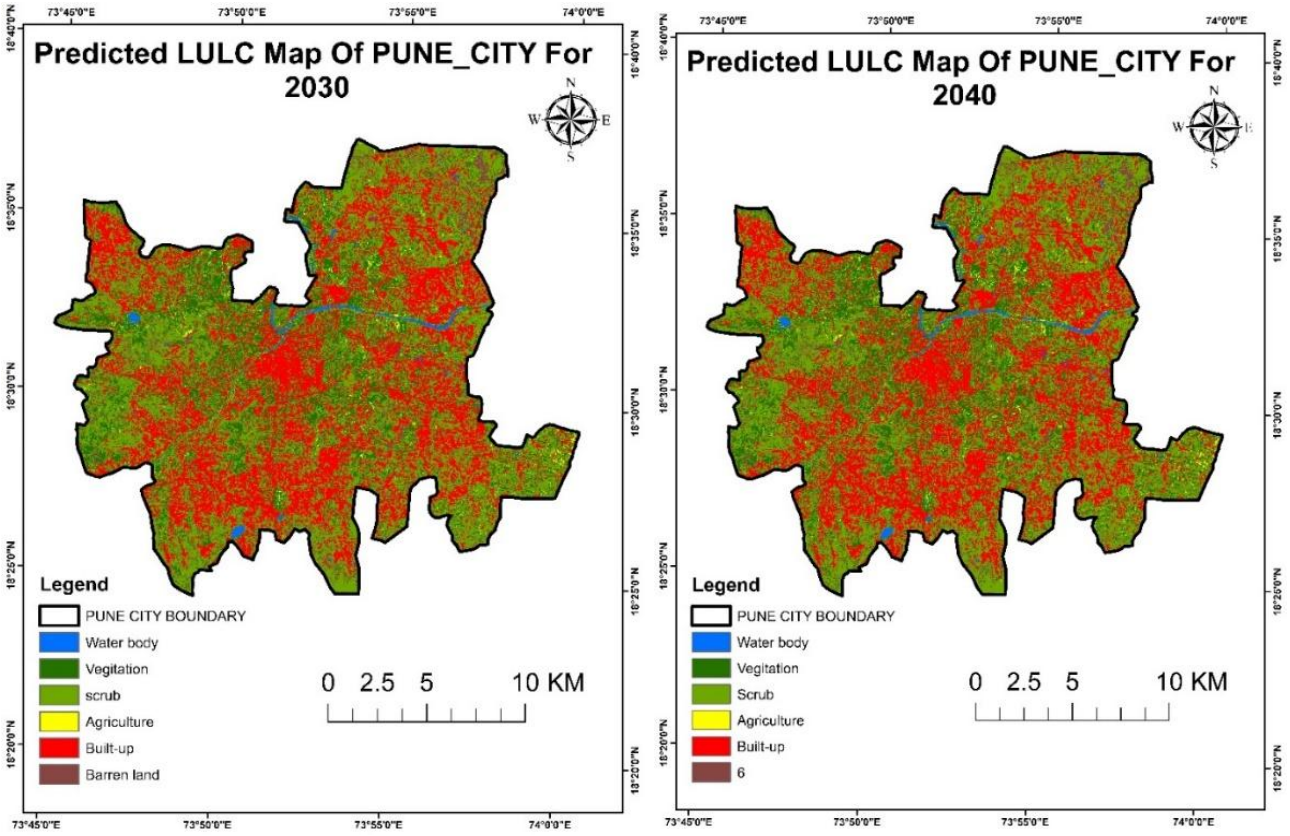


Figure 6. Predicted LULC maps for the year 2030 and 2040.

4.8 Change Detection Through Predicted Years:

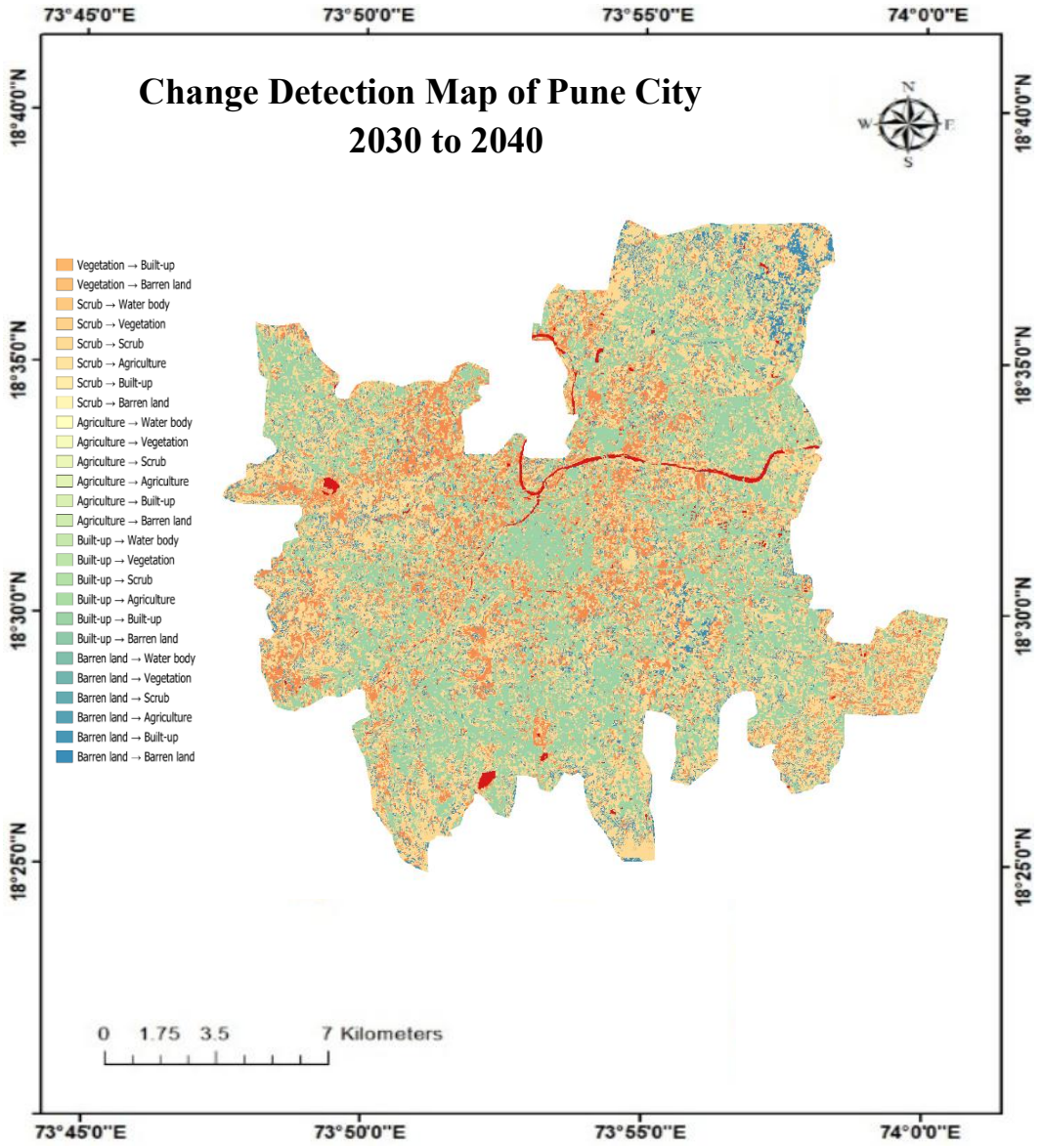


Figure 7. Change Detection 2030 – 2040 map.

The chart shows that the change in LULC of Pune between 2030 and 2040 has shown only slight transitions among the land-cover classes. The built area (BU) is reflective of a slight (0.01km2, -0.002%) decrease, but it still covers some 32 percent of the overall area. The scrub land (SB) is increasing by a small amount of 0.54km 2 (0.15%), and it is still the predominant type which occupies about 43 per cent. Vegetation (VN) loses a little by 0.14 km 2 (0.04%), and water bodies (WB) lose a little by 0.03 km 2 (0.008%). Likewise, agricultural land (AR) can be observed to reduce only slightly (0.02 km 2) (−0.006) and barren land (BL) reduces by 0.34 km 2 (−0.09). In general, the estimated LULC curves will imply rather stable land-use situations with slight variations in space, which means that urbanisation in Pune could be at the stage when the intensification of land-use is more relevant than a significant spatial growth.

Table 5. 2030 – 2040 total change.

Classes	2030 Sq. km	2040 Sq. km	Total Area Changed Sq. km	2030%	2040%	Total %
WB	3.51	3.48	-0.03	0.97%	0.96%	-0.008%
VN	54.50	54.36	-0.14	15.16%	15.12%	-0.04%
SB	155.72	156.26	0.54	43.31%	43.46%	0.15%
AR	3.50	3.48	-0.02	0.97%	0.96%	-0.006%
BU	114.65	114.64	-0.01	31.89%	31.88%	-0.002%
BL	27.61	27.28	-0.34	7.68%	7.58%	-0.09%

5.

Conclusion:

This study has discussed the changes in LULC over a period of time and modelled future land-use of Pune by simulating with the help of multi-temporal satellite imaging and ANN-based CA MOLUSCE modelling framework. The discussion showed that there was serious urban sprawl in the previous years, especially between 2015 and 2020, and the future outlooks show that land-use developments are going to be relatively stable but with small variations. Its high success in prediction proves that the modelling method is excellent in explaining the trend of urban growth and in promoting sustainable urban development The research study is limited by the few driving factors and medium resolution satellite series. It may be possible that socio-economic indicators, policy variables, and greater spatial resolution data, and more advanced machine-learning models can be included in future studies to get a higher level of reliability of the prediction and to draw more detailed conclusions about the long-term engagement of the urban sphere and its environmental conditions.

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